

# Determination of Various Diseases in Two Most Consumed Fruits using Artificial Neural Networks and Deep Learning Techniques

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## ABSTRACT

Fruit diseases are manifested by deformations during or after harvesting the components in the fruit, when the infestation is caused by spores, fungi, insects or other contaminants. In early agricultural practices, it is thought that non-destructive examination is possible with the analysis of pre-harvest fruit leaves and early diagnosis of the disease, while post-harvest detection and classification of fruit disease is possible by evaluating simple image processing techniques. Diseases of rotten or stained fruits without destruction. In this way, the disease will be identified and classified and the awareness of the producer for the next harvest will be provided. For this purpose, studies were carried out with apple and quince fruit, images were determined using still fruit pictures and machine learning, and disease classification was provided with labels. Image processing techniques are a system that detects disease made to a real-time camera and prints it on the screen. Within the scope of this study, the data set was created and images of 22 apples and 18 quinces were taken. The image was classified by similarities in the literature review. The success of the proposed Convolutional Neural Network architecture in recognizing the disease was evaluated. By comparing the trained network, AlexNet architecture, with the proposed architecture, it has been determined that the success of image recognition has increased with the proposed method.

**KEYWORD:** Fruit Diseases; Image Processing; Machine Learning; KNN; Deep Learning; CNN

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## I. INTRODUCTION

Fruits, one of the important issues of the food industry, constitute a large part of the crop production cycle. The spoilage of fruits is one of the factors that the consumer does not prefer at the point of final consumption and when encountered, the shopkeepers who offer the product to the end consumer lose their reputation in the eyes of the consumer. As with other plant-based food products, this spoilage indicates a disease. Sick products that are not preferred by the end consumer are returning with a great economic loss for fruit producers. When the producer cannot fulfill the necessary combat activities, it is economically damaged due to the increase in product loss.

It reflects the importance of detecting diseases in agricultural products in order to prevent losses in the food sector from producers to transporters, from food wholesalers to retailers, which have economic efficiency in agricultural production. Deformations in agricultural products often cause the final consumer to approach cautiously up to the point where the product is defective. As with most herbal products, fruit diseases also cause deformities. At this point, the use of expert systems used in the detection of various diseases such as shape changes in the organs of the human body, tumor cell detection by image processing techniques suggests that it may be possible to

prevent the disease. from the very beginning, in the production phase. This system design is a design system in which a camera is used to achieve diagnosis with three-dimensional (2D) representation [1].

Disease recognition designs provide a very limited resource for the detection of fruit diseases in the literature. Wen and Tao, (1997) considered one of the first studies in this field. For the fresh market, OECD standards have developed a system for estimating fruit quality by grading by size, color and surface defects. While size and color grading is now automated, a system for automatically detecting surface defects in Golden Delicious apples has been developed to separate damaged fruit and has automatic color grading. This is based on a model that assumes that the apple is spherical of variable diameter with respect to fruit size. The system can analyze more than five fruits per second per grading line. Streak tests showed that 69% of fruits were graded correctly, but 26% were graded just above or below the correct grade[2].

In this study, 22 apples and 18 quince images were used for this analysis made with still pictures. Data magnification was provided by using image reproduction techniques. The success rate in detecting the disease was determined to be

83%, and the test was applied in two stages and the success result in the K-Nearest Neighbor (K-NN) method was found 81% among the classes determined in the data set.

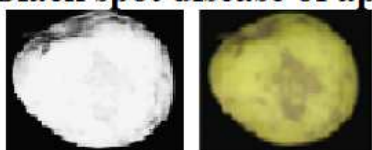
The main purpose of this study is to facilitate the detection of fruit diseases. For this purpose, it is to design a real-time image recognition system using convolutional neural networks (CNN), which is a deep learning architecture. The same system was created with the AlexNET architecture, which has a different architecture in the same deep neural network, and its successes were compared with the network created within the scope of this study.

## II. Data Set Creation

The number of studies in which image recognition techniques are provided for the detection of fruit diseases worldwide is limited. The most important reasons for this are; There are no ready-made data sets for various studies and the data sets created are not comprehensive.

In this study, a data set of 5 classes was created for apple using 600 images taken from two different fruits, and a data set of 2 classes was created for quince. These are 5 fruit diseases for apple[3]: black spot disease, alternaria disease, worm, powdery mildew of apple, for quince: brown rot on quince and blue mold rot on quince[4]. A, each pattern has two different images in black and white (binary) and color (RGB). 5/6 of the data was used for training, 1/12 for verification and the rest for testing. In Figure 1. colored and binary patterns are given for the sample two classes.

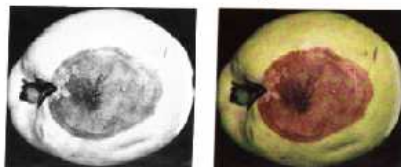
### Black spot disease of apple



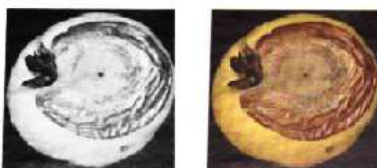
### Alternaria disease of apple



### Brown rot on quince



### Blue mold rot on quince

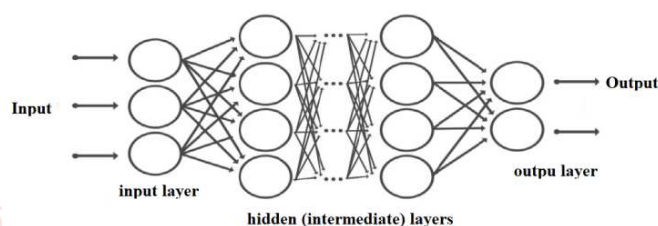


**Figure 1** Black-white and color pictures of apple and quince diseases patterns(The data set we created was taken with Samsung Galaxy J7 Pro and transferred to Intel® Core™ i7-8750h CPU @ 2.20 Ghz and 16.00 GB RAM Nvidia GTX 1050 ti Video Card and Microsoft Windows 10 Home x64 bit operating system via intermediate cable.)

## III. Methods Used

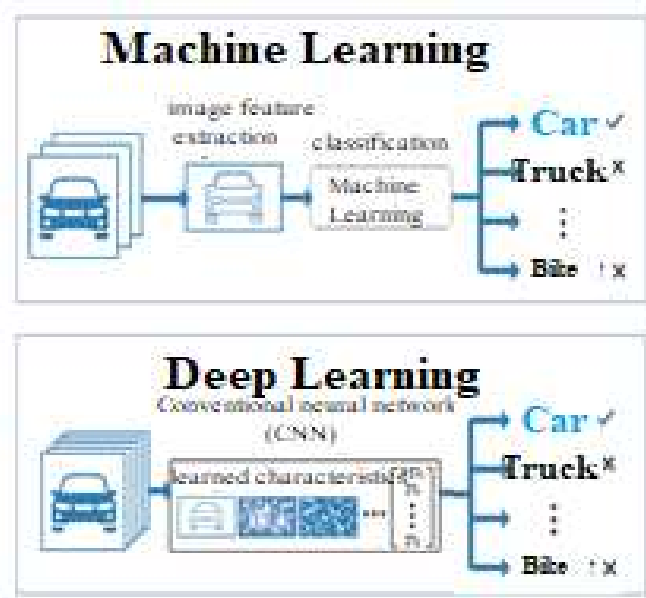
### A. Deep Learning

Deep Learning; Learning an artificial intelligence method that basically uses multiple artificial neural networks, which is used for many purposes such as natural language processing, pattern recognition, speech recognition, is one of the types of machine learning. This method was first used in 2006 in Hinton et al. He used a very long-term learning term [5] and when he was together at Aizenberg in 1999; It has been described in detail as a nerve from the term deep learning. [6] The expression Deep here refers to the number of layers in the network, the more layers the more the deeper the network is, the more processing technology for computers and the ability to do more expensive money calculations have made learning with graphics cards learning. Figure-2 shows a simple deep learning model.



**Figure 2** General deep learning model

Since the deep learning method has an artificial neural network structure, it is also called deep neural networks. One of the most important features of this structure is that it can perform both feature extraction and classification process itself, and it can be used only in feature extraction and then with another classifier. Also, they can be programmed in parallel with deep neural networks, reducing the processing time. Otherwise, it may take much longer to process enormous data.



**Figure 3.** Classical machine learning methods and comparison of learning[7].

Convolutional neural networks proposed by Lecun et al. In 1998 are more suitable for 2-dimensional data such as images. Each latent convolution filter transforms its input into a 3-dimensional output of neuron activations. It was developed inspired by the neurobiological model of the visual cortex while creating convolutional neural networks. In this sense, this network structure is more effective in visual object

recognition. There are many different models for convolutional neural networks. Model selection is an important factor in solving the problem. There are many successful models designed to distinguish pictures. These are mainly Lenet, Alexnet, Googlenet and Resnet. Together with the CNN we created, we chose the AlexNET model designed by Alex Krizhevsky and his group, which has a deeper network structure than the one based on Lenet architecture, which reduced the error rate from 26% to 15% in the Image net competition in 2012. [7]

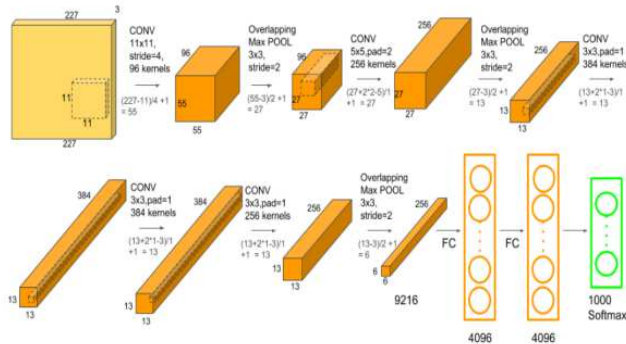


Figure 4 AlexNet Architecture [7]

As seen in Figure 4, this architecture basically consists of 5 convolutional layers and 3 fully connected layers. Since there are 1000 objects in the classification layer, it consists of 1000 neurons. Filter sizes in convolution layers are 11x11, 5x5, 3x3. Activation function ReLu, max pooling in pooling layers used to reduce the number of parameters, and momentum Skoastic Gradient Descent (SGD) in optimization was selected. This model, which operates on a dual GPU (Graphics Processing Unit), calculates approximately 60 million parameters. [7]

#### IV. Made Works

Two different CNN models were used in this study. Black and white images of 50x50 pixels were used in the entrance layer of the CNN structure we created. In the first convolution layer, 16 filters of 2x2 size were used. In the second convolution layer, 32 filters of 5x5 size were used. In the third convolution layer, 64 filters of 5x5 size are used and there are two fully connected layers. The CNN architecture and parameters created in Figure 5 can be seen.

The first training of the CNN structure created within the scope of this study took approximately 2.5 hours. Since there is a deeper network in the AlexNet structure and RGB images are used, the training phase took 4.5 hours. The epoch number 20 was chosen for both structures.

The system was developed on Intel ® Core™ I7 -8750h CPU @ 2.20 Ghz and Nvidia GTX 1050 ti Video Card with 16.00 GB RAM and Microsoft Windows 10 Home x64 bit operating system computer. Compared to other programming languages, Python language was chosen because it allows to write the program code with the least effort and fast, and the software was written using the tensorflow library in JetBrains PyCharm Community Edition 2019 1.1 environment.

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 49, 49, 16)	80
max_pooling2d_1 (MaxPooling2D)	(None, 25, 25, 16)	0
conv2d_2 (Conv2D)	(None, 23, 23, 32)	4640
max_pooling2d_2 (MaxPooling2D)	(None, 8, 8, 32)	0
conv2d_3 (Conv2D)	(None, 4, 4, 64)	51264
max_pooling2d_3 (MaxPooling2D)	(None, 1, 1, 64)	0
flatten_1 (Flatten)	(None, 64)	0
dense_1 (Dense)	(None, 128)	8320
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 22)	2838
Total params: 67,142		
Trainable params: 67,142		
Non-trainable params: 0		

Figure 5 CNN architecture that occurs in Tensor flow

Again, as another CNN structure in this study; The pre-trained AlexNet model is used. Thanks to the use of the AlexNet structure, changes were made only in the classification layer without creating CNN layers. Since this structure was previously trained; By applying the learned filters to the data set consisting of fruit images, the features were extracted and the classification process was carried out. In the input layer of the AlexNet structure, unlike the other CNN models, a data set consisting of 227x227x3 pixel color (RGB) images is used.

The system cuts the image of the diseased fruit placed in the dark blue selected area through the web camera as shown in Figure 6, gives it to the trained system and prints the character with the highest predictive value and the score value.

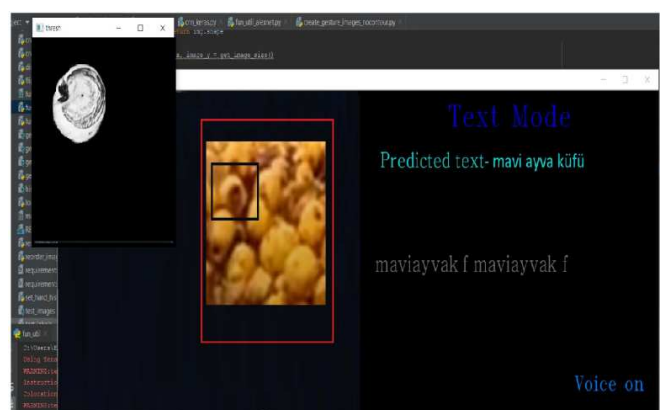


Figure 6.Screen image of real-time patient fruit recognition system



Two different CNN architectures are used in this study. The accuracy value of the test data applied to the AlexNet model was obtained as 81.3%. In the CNN architecture proposed in this study, more successful results were obtained with an accuracy of 83.3%. The confusion matrix results obtained in the proposed CNN architecture are given in Table 1.

[ [69
[ 0 61
[ 0 0 67
[ 0 0 0 70
[ 0 0 0 0 60
[ 0 0 0 0 0 69
[ 0 0 0 0 0 0 67
[ 0 0 0 0 0 0 0 50
[ 0 0 0 0 0 0 0 0 57
[ 0 0 0 0 0 0 0 0 0 82
[ 0 0 0 0 0 0 0 0 0 0 73
[ 0 0 0 0 0 0 0 0 0 0 0 65
[ 0 0 0 0 0 0 0 0 0 0 0 0 66
[ 0 0 0 0 0 0 0 0 0 0 0 0 0 75
[ 0 0 0 0 0 0 0 0 0 0 0 0 0 0 61
[ 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 65
[ 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 66
[ 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 70
[ 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 64
[ 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 64
[ 0 76
[ 0 64
[ 0 72]

**Table 1 CNN Confusion Matrix**

The reason why the Alexnet network structure is less successful is that the input images are rgb, so the depth has tripled, so our network should be deeper or trained with more epochs rather than keeping the number of epochs the same.

## V. Conclusion

Fruit diseases affect the whole society, from the producer to the end consumer. In this preliminary environment, a CNN was designed for real-time detection of fruit disease to reduce economic losses in the early stages of disease

detection, fruit production, distribution, and final breeding delivery. The data set was created by defining 5 classes of apple disease and 2 classes of quince disease within the scope of this study. The models created for this were determined by comparing them with two-stage architecture trained with disease images. To achieve real-time tests and successful research results, the data set will be expanded in the future and a video-based identification system will be created to identify other fruit diseases.

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